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New Meteosat Pattern Recognition Products for Use in Weather Forecasting

by

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Abstract

A scheme is currently being devised at the UK Met. Office to identify cloud fields and synoptic scale cloud systems using pattern recognition techniques, in an effort to find new observational products which might be assimilated into numerical weather prediction (NWP) models. The scheme uses artificial neural networks at three different scale lengths to calculate appropriate spectral, textural, spatial and contextual features. This paper presents results from one of the networks, which uses simple spectral features to obtain a classification by airmass into one of clear, dynamic, shallow or deep convection. The network was trained using 2190 Meteosat visible and infrared samples taken during the course of 1994, validated from UK Met. Office analyses. A product from the airmass classifier is described, already in use in a trial operational version of a thunderstorm flood forecasting system. The assimilation of similar products into NWP models is discussed, including discriminators of cloud fields, synoptic scale cloud systems and objectively labelled parameters such as precipitation rate.

Introduction

Much of the analysis of cloud observed in conventional satellite imagery has in the past been performed in terms of individual albedo values and infrared brightness temperatures, obtained on a pixel-by-pixel basis (Rossow *et al.*, 1985). Meteorologists can, however, obtain a much greater amount of information from the imagery, in terms of cloud fields and their relation to other cloud fields, familiar areas of land, the location and shape of synoptic scale cloud systems, time of the day and year and so on. Not only are they using spectral features to identify objects in the imagery, but also textural, spatial and contextual information.

With these ideas in mind, the Satellite Image Applications Group (SIAG) at the UK Meteorological Office began a study to examine a variety of pattern recognition techniques, using all of these key features, for both cloud field (e.g. cirrus, cumulonimbus) and cloud system (e.g. depression, cold front) identification (Pankiewicz, 1995), the eventual goal being to develop new observational products for assimilation into NWP models. The study concluded that one of the best pattern classifiers available at present is the multilayer perceptron (MLP) artificial neural network. It has gained wide acceptance in the remote sensing community, and has been used with success in a number of cloud field classification schemes (Lee *et al.*, 1990, Welch *et al.*, 1992), and an early synoptic scale cloud system classifier (Peak and Tag, 1992). There are a number of reasons for choosing MLP networks as opposed to traditional classification tools, such as the lack of dependence on parameterised distributions, the ability to solve nonlinearly separable problems, and the high classification speed and accuracy.

It was decided to use the bottom-up approach described by Peak and Tag (1992) to first classify small scale cloud field samples, the eventual aim being to classify synoptic scale cloud systems. To make this task simpler, a classifier designed to identify cloud types *associated with different airmasses* was built, resulting in a three-level cloud classification scheme (Pankiewicz, 1995). The advantage of such a method is that it uses different features at appropriate scales: spectral features in the smallest scale classifier, then textural features and finally shape, size and context at the largest scale.

This paper describes how this first airmass classifier was built, and how it was incorporated into GANDOLF (Generating Advanced Nowcasts for Deployment in Operational Land-based Flood forecasts), a thunderstorm flood forecasting system designed to provide automated precipitation forecasts and warnings to the UK Environment Agency. Other classifiers currently being evaluated are briefly described, including the second classifier of the three-level scheme using textural information, and a classifier which estimates rainfall rate from NOAA AVHRR imagery using radar ground truth data for training, but which can be easily used for Meteosat rainfall estimation.

Airmass Classification

Instead of training a classifier on cloud field samples labelled from a *purely* subjective

point of view (cirrus, stratus etc.), it was decided to label a set of samples according to the nature of the airmass present, by comparing the airmass that a meteorologist would expect from the imagery with the corresponding analysis chart, so giving more confidence in the labels. Samples were broadly divided into a total of 3 airmass classes where cloud was present: dynamic (frontal cirrus, thin cirrus, altostratus, nimbostratus, stratus, fog and haar), shallow convection (stratocumulus and cumulus) and deep convection (cumulonimbus and mesoscale convective systems), plus a 4th clear class otherwise. This provided the basis for the small scale classifier described above. This meant that labels would be more representative of a physical process in the atmosphere rather than, for example, differentiating between the subtleties of cumulus and stratocumulus.

The UK Met. Office's Autosat-2 processing system (Allam *et al.*, 1990, now superseded by Autosat-3) obtained both NOAA AVHRR and Meteosat imagery between 1990 and 1996, and provided a number of image products in polar stereographic coordinates including albedo (normalised by the cosine of the solar zenith angle) and infrared brightness temperature. SIAG has been archiving such imagery on a daily basis from specific areas of the world, but mainly northwest Europe and the Atlantic Ocean, since May 1992.

A subset of 365 Meteosat visible and infrared images, one for each day of the year in 1994, was selected at random from a period within 2 hours of local sunrise and sunset at the image centre. For the area chosen, the reprojected and processed pixel dimensions are 3.84km for Meteosat at 60°N. A total of 6 samples were chosen per day (2190 for the whole year), by Clive Pierce, a meteorologist at the UK Met. Office, using surface analyses to verify airmass information. Each sample consisted of a box of 17x17 pixels, to ensure sufficient statistics and to be suitably large enough to provide information on the airmass in the sample, and were labelled into one of the 4 airmass classes described above. The distribution of samples obtained in this way reflected the true *a priori* distribution of samples in the imagery, of significance when used in training neural networks (Foody *et al.*, 1995).

The standard backpropagation learning algorithm (Rumelhart *et al.*, 1986), was used to train the MLP neural network, which consisted of 10 input nodes representing 7 simple spectral features, 2 temporal features and a bias node, 12 hidden nodes, and 4 output nodes representing the airmass classes. The 7 spectral features were chosen because of their proven capability at discriminating cloud (Gu *et al.*, 1991; Bankert, 1994) and by looking at the class distributions obtained from the training samples. They included the visible minimum, maximum, standard deviation and Roberts' gradient (a function used in image processing to enhance edges), and the infrared maximum, ratio of maximum to minimum and standard deviation. In addition, the month of the year and hour of the day were chosen, although these were found to provide only second order discriminating features. All features were normalised to the range 0 to 1.

The rate of adaption of weights was set to a value of 0.9, a sigmoidal thresholding function was used with a spread of 1.0, and the network was examined every 5 epochs

(cycles through the complete training data) to check the mean square error at the output layer. When this reached a value of less than 10^{-5} for more than 10 consecutive epochs, or when a maximum of 200 epochs had passed, training was stopped. Training samples were taken from a subset of 1460 samples from the original 2190, with the remaining 730 being used as independent test samples. When a good solution was obtained, the network was tested 10 times on a selection of the 730 test samples, in order to provide an estimate of the standard deviation of the classification accuracy. A classification rate of 80.8±2.2% was obtained in this way, and the best confusion matrix obtained from that network is shown in table 1.

	Cl	Dy	Sh	De
Clear	50	0	0	0
Dynamic	8	35	7	0
Shallow	0	2	42	6
Deep	1	4	4	41

Table 1: Airmass Classification Accuracy. The best confusion matrix obtained for the airmass classifier with an accuracy of 84.0%. Rows represent the truth from the labelled samples, and columns are the network estimates (class names abbreviated).

The main problems encountered are the misclassification of dynamic cloud into clear or shallow convective classes, representing particular samples of thin cirrus and stratocumulus respectively (amounting to 7.5% of the error in the example in table 1). Misclassification errors between shallow and deep convection amount to 5.0%, but are unimportant if convection is required as a single class. Four deep convective samples are "misclassified" as dynamic cloud, but this turns out to be a useful feature of the network. Centres of large cumulonimbus clouds (mesoscale convective systems) tend to be classified as dynamic, as the satellite is observing thick cirrus, whereas edges are nearly always classified as deep convection. This has the effect of giving a conservative measure of deep convection, useful in GANDOLF.

Use Of The Airmass Classifier In GANDOLF

The main requirement of the GANDOLF system is to provide the UK Environment Agency with good precipitation forecasts. Since the main sources of error in flood forecasting arise during periods of heavy convective precipitation, the UK Met. Office has devised a new technique using conceptual models of convective cells to identify growing and decaying areas of convective activity (Hand, 1996). As well as this forecast model, a precipitation forecast for dynamic situations based on extrapolation is used, obtained from the UK Met. Office's Nimrod nowcasting system (Golding, 1994). The problem was in deciding whether the situation was predominantly dynamic or convective.

Originally, a technique involving fields of convective available potential energy and helicity was used, derived from the UK Met. Office's Mesoscale Model, to discriminate the two situations. However, these proved to be unsatisfactory either individually or in combination (Pierce *et al.*, 1995). In comparison, the airmass classifier was found to give much greater reliability. Since no discrimination of shallow or deep convection is required, the accuracy of 81% improves to around 86% (87.7% in table 1). The airmass classifier was used in this way in a trial operational version of GANDOLF from May to October 1996, and at the time of writing, the results were being assessed, with the expectation that GANDOLF would become fully operational after April 1997. A detailed description of the use of the classifier in GANDOLF is given by Pankiewicz (1997).

Current And Future Research

Work is currently under way to produce a second scale classifier, capable of providing a robust identification of cloud fields. Since cloud structure in different airmasses is present at different scales, a filter is being used to calculate textural features over circular areas whose diameter depends on the initial airmass classification. Clear regions have texture computed over a small area, whilst deep convective regions have texture obtained from an area of 25 pixels radius. The cloud field classification can then be used to produce a field of relative humidity profiles from a look-up table, one profile per cloud field class, in a similar way to the scheme of Mills and Davidson (1987), producing a new observational product which might be assimilated into NWP models. Synoptic scale cloud system information will be more difficult to assimilate, since the product needs to be in a form similar to that of a model field. One possibility is to extract information about synoptic scale systems from the model through pressure and relative humidity fields to define, for example, the position of fronts. A comparison with the imagery product could then be made to determine whether the forecast evolution of particular features is too slow or too fast (Hoffman *et al.*, 1995).

In addition to cloud detection, a study has recently been completed using feature selection and neural network classification to estimate precipitation rates from satellite imagery. This field is notoriously difficult, with poor results often being obtained in mid-latitude regions (Jackson *et al.*, 1995). In the study, 105 spectral and textural features, the latter including grey-level difference vectors (GLDVs), were calculated on over 1400 samples of NOAA AVHRR data taken during the 2nd Algorithm Intercomparison Project (WMO, 1994). These image sets coincide with radar ground truth data in the form of precipitation rates, all taken during March and April 1991 over northwest Europe. Knowing the rainfall classes belonging to each satellite imagery sample, the 105 feature values were calculated and compared using the Fisher, Bhattacharyya and the Transformed Divergence probabilistic distance measures (Gu *et al.*, 1991), in multidimensional feature spaces with feature vectors varying in dimension from 1 to 9.

An 8 dimensional feature vector was found to obtain the best overall results, and consisted of the mean angular second moment in channel 3, the mean and maximum

contrast in channel 3 (all GLDVs), the minimum, maximum and range in channel 5 and the mean angular second moment and contrast in channel 5. Initial results on individual AVHRR swaths have achieved a false alarm ratio of 0.03±0.02% and a probability of detection (hit rate) of 0.72±0.10%, a significantly better result than previous AVHRR algorithms (Jackson *et al.*, 1995). Future work will be aimed at applying these techniques directly to Meteosat imagery, using a more complete set of ground truth data to identify the most significant features from a set larger than the 105 considered in this pilot study.

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